

Improving Implicit Semantic Role Labeling by Predicting Semantic Frame Arguments

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Abstract

We introduce an approach to implicit semantic role labeling (iSRL) based on a recurrent neural semantic frame model that learns probability distributions over sequences of explicit semantic frame arguments. On the NomBank iSRL test set, the approach results in better state-of-the-art performance with much less reliance on manually constructed language resources.

1 Introduction

Semantic role labeling (SRL) has traditionally focused on semantic frames consisting of verbal or nominal predicates and *explicit arguments* that occur *within* the clause or sentence that contains the predicate. However, many predicates, especially nominal ones, may bear arguments in discourse (Ruppenhofer et al., 2010; Gerber et al., 2009). These arguments, called *implicit arguments*, are resolved by another semantic task, Implicit Semantic Role Labeling (iSRL). Let us borrow a NomBank (Meyers et al., 2004) annotation example from Gerber and Chai (2012):

A SEC proposal to ease [A₁ reporting] [PRED requirements] [A₂ for company executives]...

The NomBank role set for *requirement* includes A0, the *requirer*, A1, the *thing required*, and A2, the *thing being required*. In the example above, NomBank does not annotate an A0. However, a reasonable interpretation of the sentence is that the *SEC* plays the *requirer* role. Such an implicit argument is known as an implicit semantic role, and identifying such roles is the focus of this paper.

As an emerging task, implicit semantic role labeling (iSRL) faces a lack of resources. First, manual implicit role annotations for use as training data are seriously limited: the one existing NomBank-based dataset covers just ten predicates (Gerber and Chai,

2010). Second, most existing iSRL systems depend on other systems (named entity taggers, explicit semantic role labelers, etc.), and as a result need not only iSRL annotations, but annotations for all of their sub-systems as well.

Several approaches have attempted to address this lack of resources. Roth and Frank (2015) generated additional training data for iSRL through comparable texts, but the resulting model performed below the previous state-of-the-art Laparra and Rigau (2012). Laparra and Rigau (2013) proposed an approach that did not require any manual iSRL annotations, based on exploiting argument coherence over different instances of a predicate, but this method required a large set of manually-constructed resources: explicit SRL annotations, WordNet super-senses, named entity annotations, and a manual mapping from SuperSenseTagger semantic classes to general semantic categories. Schenk and Chiarcos (2016) aimed at a simpler strategy that would not rely on manual iSRL annotations, requiring only an existing corpus of explicit SRL annotations: induce prototypical roles from large amounts of explicit SRL annotations and distributed word representations. However, the model performance was almost 10 points lower than the state-of-the-art Laparra and Rigau (2013).

We propose an iSRL approach that works in the low-resource setting of Schenk and Chiarcos (2016), but improves state-of-the-art performance by predicting *selectional preferences* learned through a recurrent neural semantic frame model that learns probability distributions over sequences of explicit semantic frame arguments.

2 Neural Semantic Frame Model

Our goal is to use unlabeled data to acquire selectional preferences that characterize how likely a phrase is to be an argument of a semantic frame. We rely on the fact that current explicit SRL sys-

tems achieve high performance on verbal predicates, and run a state-of-the-art explicit SRL system on unlabeled data. We then construct a predictive recurrent neural semantic frame model (PRNSFM) from these predicted frames and roles.

Our PRNSFM views semantic frames as a sequence: a predicate, followed by the arguments in the order they appear in the text, and terminated by a special EOS symbol. The model’s task is to take a predicate and zero or more arguments, and predict the next argument in the sequence, or EOS if no more arguments will follow. We draw predicates from PropBank verbal semantic frames, and represent arguments with their nominal/pronominal heads. For example, *Michael Phelps swam at the Olympics* is represented as [swam:PRED, Phelps:A0, Olympics:AM-LOC, EOS], where the predicate is labeled PRED and the arguments *Phelps* and *Olympics* are labeled A0 and AM-LOC, respectively.

Formally, for each t^{th} argument of a semantic frame f , we denote its word (e.g., *Phelps*) as $w_{f,t}$, its semantic label (e.g., A0) as $l_{f,t}$, its preceding argument words as $w_{f,<t}$, and its preceding argument semantic labels as $l_{f,<t}$, where $w \in \mathbf{V}$, the word vocabulary, and $l \in \mathbf{L} \cup [\text{PRED}]$, the set of semantic labels. We denote predicates in the same way as arguments: $w_{f,0}$ and $l_{f,0}$. Our model then aims to estimate the conditional probability of the occurrence of $w_{f,t}$ as semantic role $l_{f,t}$ given the preceding argument words and their labels:

$$P(w_{f,t}:l_{f,t}|w_{f,<t}:l_{f,<t})$$

We use a recurrent neural network to learn this probability distribution over sequences of semantic frame arguments. For a semantic frame f with N arguments, at each time step $0 \leq t \leq N$, given the input $w_{f,t}:l_{f,t}$, the model computes the distribution $P(w_{f,t+1}:l_{f,t+1}|w_{f,<t+1}:l_{f,<t+1})$ and predicts the next most likely argument (or EOS). During training, model parameters are optimized by minimizing prediction errors over all time steps.

We consider two versions of this model that differ in input (\mathbf{V}_{in}) and output (\mathbf{V}_{out}) vocabularies.

2.1 Model 1: 1-1 LSTM Model

Model 1 treats the word and semantic label as a single unit in both input and output layers. For example, *Phelps:A0* would be a single value. Our model consists of three layers (see Figure 1(a)):

Embedding Layer is a matrix of size $|\mathbf{V}_{\text{in}}| \times d$

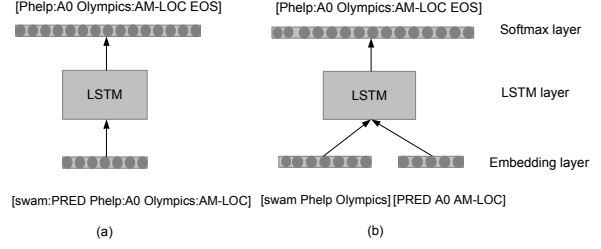


Figure 1: (a) Model 1 (b) Model 2

that maps each unit of input into an d -dimensional vector. The matrix is initialized randomly and updated during network training.

Long short-term memory (LSTM) Layer consists of m LSTM units which take as input the output of the embedding layer, x_t , and produce an output h_t by updating at every time step $0 \leq t \leq T$:

$$\begin{aligned} i_t &= \text{sigmoid}(W_i x_t + U_i h_{t-1} + b_i) \\ \hat{C}_t &= \tanh(W_c x_t + U_c h_{t-1} + b_c) \\ f_t &= \text{sigmoid}(W_f x_t + U_f h_{t-1} + b_f) \\ C_t &= i_t * \hat{C}_t + f_t * C_{t-1} \\ o_t &= \text{sigmoid}(W_o x_t + U_o h_{t-1} + b_o) \\ h_t &= o_t * \tanh(C_t) \end{aligned}$$

where W_i, W_c, W_f, W_o are weight matrices of size $d \times m$; U_i, U_c, U_f, U_o are weight matrices of size $m \times m$; b_i, b_c, b_f, b_o are bias vectors of size m ; and $*$ is element-wise multiplication.

Softmax Layer computes the probability distribution of the next argument given the preceding arguments at time step t :

$$P(w_{f,t+1}:l_{f,t+1}|w_{f,<t+1}:l_{f,<t+1}) = \text{softmax}(h_t W + b) \quad (1)$$

where W is a weight matrix of size $m \times |\mathbf{V}_{\text{out}}|$, and b is a bias vector of size $|\mathbf{V}_{\text{out}}|$. The predicted next argument is:

$$\arg\max_{w_{f,t+1}:l_{f,t+1}} P(w_{f,t+1}:l_{f,t+1}|w_{f,<t+1}:l_{f,<t+1})$$

The network is trained using the negative log likelihood loss function.

2.2 Model 2: 2-1 LSTM Model

Model 2 considers the word and the semantic label as two different units in the input layer. For example, *Phelps:A0* is considered as two separate values *Phelps* and *A0*. As shown in Figure 1(b), we use two different embedding layers, one for word values and one for semantic labels, and the two embedding vectors are concatenated before being passed to the LSTM layer. The LSTM and softmax layers are then the same as in Model 1. The

embedding layer for word values can be initialized with pre-trained word embeddings, e.g., (Mikolov et al., 2013; Pennington et al., 2014); the embedding layer for labels is initialized randomly.

2.3 Selectional Preferences

To assist an iSRL model, we extract from the PRNSFM selectional preferences that indicate how likely a word is to be an argument of a semantic frame evoked by a predicate.

Given a predicate p , arguments of the semantic frame f evoked by p can be predicted sequentially by the trained predictive model. We define the selectional preference as $P(w:l|p)$, the probability of a word w being the l argument of frame f . Our goal is to approximate $P(w:l|p)$. For each sequence q in the set of all possible argument sequences predicted by the model *before* t (S_t), we select a threshold k and generate $\text{argmax}^{k,s}$, the top k word-label pairs that have the highest probability of being the next argument. Formally:

$$\begin{aligned} S_0 &= \{[p:\text{PRED}]\} \\ S_{t+1} &= \{[q, w_{t+1}:l_{t+1}] : \\ &\quad q \in S_t, w_{t+1}:l_{t+1} \in \text{argmax}^{k,q}\} \end{aligned}$$

with $w_{f,0}:l_{f,0} = p:\text{PRED}$. For each sequence $q = [p:\text{PRED}, w_1:l_1, w_2:l_2, \dots, w_t:l_t] \in S_t$, with $t \geq 1$, we define $P(p:\text{PRED}) = 1$ and compute the probability of the sequence as:

$$\begin{aligned} P(q) &= P(w_t:l_t|w_{t-1}:l_{t-1}, \dots, p:\text{PRED}) \\ &\quad \times P(w_{t-1}:l_{t-1}|w_{t-2}:l_{t-2}, \dots, p:\text{PRED}) \\ &\quad \times \dots \\ &\quad \times P(w_1:l_1|p:\text{PRED}) \end{aligned} \quad (2)$$

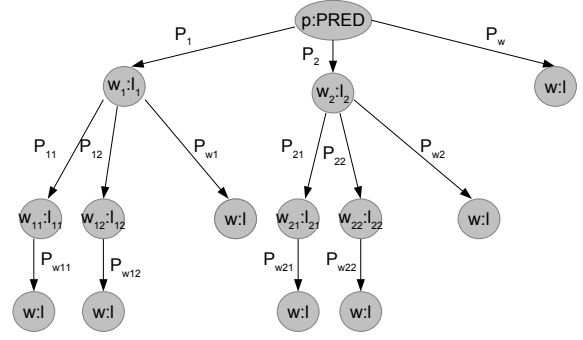
Our goal, $P(w:l|p)$ is approximated as the sum of probabilities that $w:l$ is predicted by our model at all time steps t up to a threshold T :

$$\begin{aligned} P(w:l|p) &\approx \sum_{0 \leq t \leq T} P(w:l|w_{f,<t+1}:l_{f,<t+1}) \\ &\approx \sum_{0 \leq t \leq T} \sum_{q \in S_t} P(w:l|q) \times P(q) \end{aligned}$$

where $P(w:l|q)$ and $P(q)$ are computed by Equation 1 and Equation 2, respectively. An example of the calculation of $P(q)$ is shown in Figure 2.

3 Implicit Semantic Role Labeling

Using only an explicit SRL system, we extract selectional preferences from our PRNSFM as following: For each triple of a nominal predicate np , a word candidate w , and a label l , the selectional preference score of w to be the implicit argument



Time 0: $S_0 = \{[p:\text{PRED}]\}$

Time 1: $S_1 = \{[p:\text{PRED}, w_1:l_1], [p:\text{PRED}, w_2:l_2]\}$

Time 2: $S_2 = \{[p:\text{PRED}, w_1:l_1, w_{11}:l_{11}], [p:\text{PRED}, w_1:l_1, w_{12}:l_{12}], [p:\text{PRED}, w_2:l_2, w_{21}:l_{21}], [p:\text{PRED}, w_2:l_2, w_{22}:l_{22}]\}$

$P(w:l|p) \sim P_w + P_{w1}P_1 + P_{w2}P_2 + P_{w11}P_{11}P_1 + P_{w12}P_{12}P_1 + P_{w21}P_{21}P_2 + P_{w22}P_{22}P_2$

Figure 2: Selectional Preference Inference example: $k=2, T=2$. The possible sequences are represented as a tree. Each arrow label is the probability of the target node to be predicted given the path from the tree root to the parent of the target node.

role l of np is approximated as:

$$P(w:l|np) = \max_{p \in V(np)} P(w:l|p)$$

where $P(w:l|p)$ is the selectional preference score produced by our PRNSFM, and $V(np)$ is set of verbal forms of np . For example, for the noun *funds*, $V(\text{funds}) = \{\text{funds}, \text{fund}, \text{funding}, \text{funded}\}$.

We apply selectional preferences to iSRL in a similar way to (Laparra and Rigau, 2013). For each nominal predicate np and implicit label l , we consider a “context window” of the previous two sentences and the current sentence. Each sentence in the context window is annotated with the explicit SRL system. If there are any other instances of np or $V(np)$ in the text that have an explicit argument of type l , deterministically predict the closest such argument as the implicit l argument of np . Otherwise, run the PRNSFM over each word in the context window, and select the word with the highest selectional preference score above a threshold s . We optimized this threshold on the development data, resulting in $s = 0.0003$.

As in Laparra and Rigau (2013), the selectional preferences can be updated by using *sentence recency factor* to emphasize recent candidates. The selectional preference score p is updated as $p' = p - z + z \times \alpha^d$ where d is the sentence distance, and α and z are parameters. We set $z = 0.00005$ based on the development set and set $\alpha = 0.5$ as in (Laparra and Rigau, 2013).

4 Experiment

4.1 Building PRNSFM

Semantic Role Labeling We use the full pipeline from MATE¹ (Björkelund et al., 2010) as the explicit SRL system. The system is retrained on the CoNLL 2009 training portion.

Unannotated Data The unannotated data includes Wikipedia², Reuters³, and Brown⁴.

Dataset for PRNSFM The first 15 million short and medium (less than 100 words) sentences from the unannotated data were annotated automatically by the SRL system. The annotated results were then used together with the gold standard CoNLL 2009 SRL training data to train the PRNSFM. To evaluate how well the system acquires knowledge from unlabeled data, we also train PRNSFM on only the gold standard CoNLL 2009 training data.

Neural network training and inference Parameters were selected using an evaluation over the CoNLL 2009 development set. We set the dimensions of word and label embeddings in the PRNSFM as 50 and 16 respectively. The hidden sizes of LSTM layers are the same as their input sizes. Word embedding layers are initialized by Skip-gram embeddings learned by training the word2vec tool (Mikolov et al., 2013) on unannotated data. Our models were trained for 120 epochs using the AdaDelta optimization algorithm (Zeiler, 2012). For fast selectional preference computing, we set $k = 1$ and $T = 3$.

4.2 Evaluation

We follow the evaluation setting in Gerber and Chai (2010); Laparra and Rigau (2013); Schenk and Chiacaros (2016)⁵: the method is evaluated on the evaluation portion of the nominal iSRL data by Dice coefficient metrics.

4.3 Results

Table 1 shows the prior state-of-the-art and the performance of our PRNSFM-based models. We include a baseline system (Skip-gram) that is trained on the same unlabeled and labeled data as the PRNSFM, but treats the predicates and arguments

| | P | R | F1 |
|--------------------------------|-------------|-------------|-------------|
| Gerber and Chai (2010) | 44.5 | 40.4 | 42.3 |
| Laparra and Rigau (2013) | 47.9 | 43.8 | 45.8 |
| Schenk and Chiacaros (2016) | 33.5 | 39.2 | 36.1 |
| Skip-gram | 26.3 | 32.3 | 29.0 |
| Model 1 (Conll 2009 only) | 39.2 | 34.1 | 36.5 |
| Model 2 (Conll 2009 only) | 40.2 | 36.0 | 38.0 |
| Model 1 (Conll 2009+unlabeled) | 48.0 | 38.2 | 42.6 |
| Model 2 (Conll 2009+unlabeled) | 52.6 | 41.0 | 46.1 |

Table 1: Implicit role labeling evaluation.

as a bag of words rather than a sequence. We also include results for training our PRNSFM on only the CoNLL 2009 data (no unlabeled data).

Our Model 2 outperforms all other models in terms of precision and F1 scores⁶. This is notable since the first two models require many more language resources than just an explicit SRL system: Gerber and Chai (2010) use WordNet and manually annotated iSRL data, while Laparra and Rigau (2013) use WordNet, named entity annotations, and manual semantic category mappings. Schenk and Chiacaros (2016), like our approach, uses only an explicit SRL system, but both of our models strongly outperform their result.

Table 1 also shows that training on large unlabeled data results in a marked improvement compared to training on only the CoNLL 2009 labeled data, evidence that the models have acquired linguistic knowledge from the unlabeled data. Moreover, the better performance of our models over the standard Skip-gram proves the effectiveness of modeling semantic frames as sequential data.

5 Conclusion and Future Work

We have presented the idea of predictive recurrent neural semantic frame models for learning probability distributions over semantic argument sequences. The predicted selectional preferences are applied to an iSRL task. Based on our evaluations on the NomBank iSRL dataset, our best model improves state-of-the-art performance while reducing the amount of language resources needed. In future work, we plan to evaluate how our predictive models can be applied to other tasks.

¹<https://code.google.com/archive/p/mate-tools/>

²<http://corpus.byu.edu/wiki/>

³<http://about.reuters.com/researchandstandards/corpus/>

⁴<https://catalog.ldc.upenn.edu/ldc99t42>

⁵ Following Schenk and Chiacaros (2016), we do not perform the alternative evaluation of Gerber and Chai (2012) that evaluates systems on the iSRL training set, since the iSRL training set overlaps with the CoNLL 2009 explicit semantic role training set on which MATE is trained.

⁶ Calculating statistical significance is challenging, because item-level predictions from the other systems are not publicly available. As an overly conservative estimate, we take a t-test over the 10 predicate-level F1 scores (available in published papers and only omitted in this draft due to space constraints). Comparing against Model 2, this yields $p=0.28$ for Gerber and Chai (2010), $p=0.46$ for Laparra and Rigau (2013), and most importantly $p=0.058$ for Schenk and Chiacaros (2016).

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